SPECIAL FEATURE

Uncertainty in Ecological Inference and Forecasting[1]

As ecologists increasingly focus on problems that entail multiple sources of stochasticity, the limitations of traditional models loom large. We can often recognize the need for stochasticity in models (the model is too simple, the process is obscure, observations have error, parameters are variable and uncertain), but statistical models provide no straightforward methods for accommodating the multiple sources. The traditional home for stochastic effects, e.g., the error term of standard linear models (regression, ANOVA, GLM, . . .), fosters a practice of shoehorning complex problems into simple experimental designs. Model testing and fitting in the rarified experimental setting can be an unsure footing for prediction in a noisy, uncertain future. Moreover, classical approaches provide no practical method for formally integrating insight that may derive from diverse sources. The high dimensionality characteristic of a model that allows for many sources of stochasticity rarely submits to classical approaches.

The 1990s saw progress in the capacity to accommodate stochasticity, particularly with the development of Markov chain Monte Carlo (MCMC) methods. These recent advances have effectively neutralized one of the primary criticisms of Bayesian approaches, i.e., that they depend on prior parameter distributions that are readily solved, but lack other motivation. More importantly, modern approaches provide flexible methods for accommodating the variability that can stem from many sources, for incorporating uncertainties, and for data assimilation. Indeed, nearly all high-dimensional problems submit to this common methodology. Modern statistical computation is providing direct links between deterministic models that describe a process of interest and the noisy, indirect, and limited data needed to parameterize them and evaluate hypotheses.

This Special Feature brings some recent methods to bear on pervasive ecological issues. It is not limited to Bayesian or MCMC approaches, but rather includes them as part of the adaptable collection that ecologists will increasingly deploy in nontraditional models. Contributions demonstrate challenges and apply new techniques to traditional ecological topics. The unifying theme involves the uncertainty and variability that can impact estimation and forecasting at a range of scales. It is appropriate to begin with the role of ecological prediction in the context of decision. Pielke and Conant relate specific examples that demonstrate the need for a broad view of the decision process. Technical considerations are but one element.

Four contributions follow that address methodology. Predictions of population growth depend on the uncertainty in parameters that are estimated as demographic rates. Ellner and Fieberg address how parameter uncertainty can be incorporated in estimates of extinction. They introduce Sobol indices as a powerful tool for identifying parameter combinations that contribute to prediction uncertainty.

Hierarchical structures allow us to organize populations, subpopulations, and individuals in a manner that is consistent with our understanding of how variability operates. Clark uses a hierarchical approach to accommodate demographic variability within populations. Standard birth rate and survival parameters are not constants that apply to all individuals. Rather, the variability among individuals that cannot be ascribed to specific causes means that vital rates are treated as variables, and not as traditional parameters. Acknowledging stochasticity makes for less informative, but more accurate predictions.

Wikle extends the hierarchical approach to address the venerable problem of population spread. The standard diffusion model is, at best, a rough portrayal of population expansion. The approach allows for process error, together with spatial and temporal variability. Because we do not observe the process of birds diffusing across the continent, but rather, samples thereof, observation errors

are included as a separate stage. By including multiple sources of stochasticity, Wikle assesses both the trends and the variability in population spread within the context of a simple population model that ecologists widely use.

Calder et al. consider time-series data and further explore observation error. They outline state space models for ecological time series, with an example of population regulation. The flexible strategy is much simpler than the classical alternatives and broadly adaptable. Among other results, they demonstrate that stochasticity associated with data and growth impact inference.

Peterson et al. return to management applications, with an example of how model uncertainty can interact with a Bayesian decision process to produce unanticipated dynamics. With a specific example, this contribution returns us to issues related to the use of model assessments and forecasts outlined broadly by Pielke and Conant. Inherent unpredictability, in this case due to nonlinear dynamics, means that ''correct'' models are not enough to ensure wise decision-making.

Brewer and Gross take up the educational challenges posed by the need to broaden training options for ecologists. While the limitations of traditional curricula in quantitative methods have long been a subject for discussion, growing demand for ecological inference and prediction as statistical computation undergoes rapid change add new dimensions to the dialogue.

By illustrating some of the promise of modern computational statistics, these contributions can also help foster realistic expectations for prediction. Plausible assessments of what is ''predictable'' will help us identify areas where forecasts are, as yet, not feasible, where research can be expected to improve understanding, and where options alternative to more complex models and unrealistic data requirements should be pursued.

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